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Airbnb Offer in Spain—Spatial Analysis of the Pattern and Determinants of Its Distribution

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Abstract: The rising number of homes and apartments rented out through Airbnb and similar peer-to-peer accommodation platforms cause concerns about the impact of such activity on the tourism sector and property market. To date, spatial analysis on peer-to-peer rental activity has been usually limited in scope to individual large cities. In this study, we take into account the whole territory of Spain, with special attention given to cities and regions with high tourist activity. We use a dataset of about 250 thousand Airbnb listings in Spain obtained from the Airbnb webpage, aggregate the numbers of these offers in 8124 municipalities and 79 tourist areas/sites, measure their concentration, spatial autocorrelation, and develop regression models to find the determinants of Airbnb rentals' distribution. We conclude that apart from largest cities, Airbnb is active in holiday destinations of Spain, where it often serves as an intermediary for the rental of second or investment homes and apartments. The location of Airbnb listings is mostly determined by the supply of empty or secondary dwellings, distribution of traditional tourism accommodation, coastal location, and the level of internationalization of tourism demand.

Keywords: peer-to-peer accommodation; sharing economy; collaborative economy; Airbnb; residential tourism; second homes; Spain

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1. Introduction

Internet platforms enabling short-term rental of private houses or rooms, called peer-to-peer (P2P) accommodation or homesharing platforms, are an increasingly popular provider of tourist accommodation. The largest of such platforms is Airbnb, with over 5 million rental offers worldwide [1]. After 10 years of its existence, Airbnb has become an important subject of research within tourism and urban studies, as well as within other fields of social sciences. Review papers [2–4] and edited books [5,6] outline some of the research topics undertaken in these studies. These include competition between peer-to-peer rentals and traditional hospitality industry [7–11], general contribution to destinations' economies [12–14], social impacts [15–18], with special attention given to the impact on housing markets [19–23], policy and regulations on P2P rental platforms [24–27], costumer satisfaction of the service provided [28–30] and the impact of these new practices on travel patterns [31].

An interesting body of research focuses on the spatial analysis of the available offer [32–35]. It allows for a geographical understanding of the phenomenon by providing insight about where it is located and which are the factors that affect its distribution. This knowledge can help to answer the big research questions that have been posed regarding urban vacation rentals and Airbnb: are P2P platforms a competition to the traditional hotel sector or do they complement its offer? Are urban vacation rentals commercialised through P2P platforms contributing to the touristification of city centres? Is it a phenomenon only affecting tourist cities?

To date, the majority of the studies analysing the distribution of Airbnb listings have focused on large cities [23,32–38]. Although the platform itself claims to contribute to the spreading of tourist activity towards peripheral districts, previously not so much visited by tourists [39], most of the studies to date agree when stating the concentration of Airbnb listings around major tourist attractions [32–34,40]. This contributes to further agglomeration of tourism mobility and the potential displacement of residents from central districts [22,23,41].

Quattrone et al. [34] prove the correlation between the number of Airbnb listings and the distance to the city centre in London. They also noticed a relation between the distribution of Airbnb listings and the socioeconomic profile of the neighbourhoods. According to their conclusions, the distribution follows a different pattern according to the type of listings considered: room or house. Airbnb rooms are located in areas populated by highly-educated non-UK born residents, whereas Airbnb houses are located in areas of high housing prices. High spatial concentration of Airbnb listings around city centres and major tourist attractions is confirmed by Gutiérrez et al. for Barcelona [33], Heo et al. for Paris [9] and by Wegmann's and Jiao's [27] for five US cities. Other papers support the idea of the complementary role played by peer-to-peer accommodation with respect to hotel supply. Gyódi [37] shows that Airbnb listings are concentrated in different areas to hotels in central districts of Warsaw. In the case of Vienna, Gunter and Önder's [36] claim that Airbnb rentals complement hotel supply by providing larger, cheap and centrally located accommodation.

Only few studies to date extended the spatial analysis of Airbnb phenomenon outside of the limits of individual cities. There are few comparative studies between cities of Europe [42,43], USA [44], and global capitals [45]. Cesarani and Nechita [46] provide the description of the distribution of Airbnb listings in Italy, pointing at their concentration in the largest cities, coastal areas, around lakes in the north of the country and in rural Tuscany. Strommen-Bakhtiar and Vinogradov [47], and Larpin et al. [48] show how Airbnb has spread from major cities towards tourist regions in Norway and Switzerland. Studies that have looked at the role of P2P accommodation in middle-sized and small towns are also scarce. Di Natale et al. [24] examined Airbnb offer of 237 small cities in Oregon, showing how the intensity of Airbnb activity and perceptions of its impacts differ between cities. Adamiak [42] analysed the numbers and structures of Airbnb listings in European cities over 100,000 inhabitants. This study shows the ubiquity of Airbnb activity, its varied role in the structure of tourism accommodation, and country-specific characteristics of the structures of offers. In addition, it points at the important role that Airbnb plays in smaller cities, particularly in Southern Europe, emphasizing the need for further studies of the impacts of Airbnb activity in these locations.

Together with France and Italy, Spain is one of the most important Airbnb markets in Europe [49]. In addition, Spain is the second largest international tourist destination [50], with a steady increase in the number of foreign visitors in the last years [32,51]. P2P accommodation is an important topic of both academic debate and media discourse in this country [32,33,51–53]. Most attention has been given to the impacts of peer-to-peer rental platforms on major cities, mostly Barcelona [32,33,54]. Airbnb activity is blamed to cause gentrification of the city centre through the "collective displacement", that is the substitution of residential life by tourism [41,55,56]. Segú [57] estimated that Airbnb has contributed to a 4% increase in housing rents in the city between 2009 and 2016. However, Blanco-Romero et al. [15] show that tourism rentals are just one of many factors causing the increase in housing prices.

Similar conclusions about the impacts of Airbnb on urban space have been presented in cases of other Spanish cities: Madrid [16,58], Palma de Mallorca [22,59] and Valencia [60]. Spatial analyses of the Airbnb offer have been conducted for Barcelona [33], Málaga [61], Madrid [58], Valencia [60,62] and in the form of comparative studies including various cities [32,63]. They all agree on the concentration of the Airbnb offers in the city centres and close to the tourist hotspots.

Studies analysing the Airbnb offer in areas other than big cities are rare in Spain, just as in other countries. Coll Ramis et al. [64] studied the Airbnb offer of a small inland municipality of Mallorca

(Lloret de Vistalegre), showing the increase in available tourist accommodation since the appearance of peer-to-peer online platforms. The study of Yrigoy [65] describes the growth of tourist accommodation offer on the island of Menorca. It notices a high concentration of Airbnb listings in urban centres, which contrasts with the concentration of traditional tourist rental houses in tourist residential areas. Both studies prove that P2P platforms play an important role in the commercialization of rental apartments in tourist areas. Eugeno-Martin et al. explore the spatial distribution of Airbnb listings in Canary Islands [66]. They found differences between various kinds of tourist areas: sun and beach, nature-based and urban.

In Spanish coastal areas, second homes form an important part of tourism accommodation. Spain is the country with the highest number of second homes in Europe [67]. They are used for private purposes by the owners, but they are also rented out to other tourists using P2P platforms. In this regard, Miranda et al. [68] consider peer-to-peer platforms to be able to offset the negative impacts of residential tourism in these areas: increase the occupancy of dwellings, reduce seasonality and dependence of local economies on construction sector. Outside of Spanish major cities and coastal areas, rural tourism has been growing steadily in the last decades and it is now an important source of income for rural communities [69]. Rural tourism is mainly based on the rental of rural houses for vacation use, which can also be mediated through new P2P platforms as Airbnb [70].

In this paper, we aim to fill the research gaps identified above by providing a spatial analysis of Airbnb listings for entire Spain. We chose this country because of high importance of tourism for its economy, and a vivid academic and popular discussion on the impacts of P2P platforms. The analysis of the entire territory of the country is particularly interesting due to the heterogeneity of models of tourism developed in different parts of Spain, and possible variety of impacts of P2P accommodation on different types of tourist areas.

Our empirical analysis consists of two stages. First, we make a comprehensive description of the spatiality of Airbnb supply in Spain. We present the distribution of Airbnb listings in autumn 2018 in the whole country, considering three different types of listings: entire homes/apartments, private rooms and shared rooms. We then compare the distribution of P2P accommodation offer and the hotel supply, as well as measure the spatial concentration and spatial autocorrelation of the density of Airbnb listings in comparison to hotel and housing supply.

In the second stage, we attempt to find the determinants shaping the territorial distribution of Airbnb supply of various kinds employing regression analysis. To this end, we formulate five hypotheses about the possible factors influencing the distribution of Airbnb offers:

1. The location of Airbnb rentals is determined by the number of homes and flats, both used as primary dwellings and nonprimary dwellings, including second homes and vacant homes and flats. In primary dwellings, residents can rent out parts of their home through Airbnb. Nonprimary dwellings can be rented out as entire properties. The higher the number of primary and nonprimary dwellings, the higher the potential number of houses and rooms to rent. Accordingly, we assume a higher concentration of Airbnb accommodation in larger cities, as they have more primary dwellings, and are usually important tourism destinations at the same time [71].
2. Airbnb offer is located in places close to the coastline, which are (apart from major cities) principal leisure tourism destinations in Spain [72]. They also have large stocks of second homes and vacation rentals [73,74].
3. Airbnb offer concentrates in areas attractive to tourists and with already established tourism sector. Therefore, there is a correlation between Airbnb supply and hotel accommodation supply, as proved by other international studies [42].
4. Airbnb serves as an additional supply of accommodation in places where the existing accommodation capacity does not satisfy the demand due to high growth in tourism arrivals or high seasonal variations [42,75].

5. Airbnb is particularly attractive for international tourists, as it provides a familiar system of search and transaction that mitigates the risk of the deal and rates the quality of the product [76]. Accordingly, Airbnb offer is bigger in areas with a high number of international tourists, or areas easily accessible for them because of proximity to airports.

The remaining part of the paper is structured as follows: in Section 2, we present data and methods that we used in the analysis. Detailed description of the procedure of collecting data about Airbnb listings is moved to an appendix. In the next section, we present the results of the analysis: the distribution of Airbnb listings, measures of concentration and spatial autocorrelation, and models explaining their location. Detailed statistics for tourist areas/sites, and supplementary tables describing regression models are placed in appendices. The last part of the paper presents conclusions and discussion of the results.

2. Materials and Methods

2.1. Data

Homesharing platforms, including Airbnb, do not provide public data on numbers and performance of their rentals. However, such information can be obtained from their webpages through web scrapping. For our analysis, we collected Airbnb data using the script published by Tom Slee [77]. In Appendix A, we provided a detailed description of the procedure of data collection, along with the discussion of possible errors, and comparison of various sources of data on Airbnb listings in Spanish cities (Table A1). We performed the data collection in October 2018, and only listings available for rent any time in the following months were saved in our dataset. We created a database containing data on 247,456 Airbnb listings. The scrapped listings are divided into three groups defined by the platform itself: entire homes/apartments (81.7% of all listings in the database), private rooms (17.7%) and shared rooms (0.6%).

To compare Airbnb supply with housing supply and tourism activity, we used data of the Spanish Statistical Office (INE) [78]. We obtained the numbers of population of each municipality for the year 2017 from the Spanish municipal register, and the numbers of dwellings in municipalities from the last population and housing census (2011). We also obtained statistics of the tourist sector (numbers of hotel rooms and hotel guests) from the hotel occupancy survey. It is a continuous survey made on monthly basis by INE. We took into account the latest published data for the year period between October 2017 and September 2018. This data is not available at the municipal level. Hence, we used the lowest available territorial aggregation for this data: tourist areas and sites.

As a proxy of the size of hotel accommodation supply at the municipal level, we used the data obtained from TripAdvisor. This Internet platform aggregates information on hotel offers from several online travel agencies, and its search engine identifies hotels in administrative borders of cities (municipalities). We manually extracted numbers of hotels for each municipality in October 2018.

2.2. Describing the Distribution of Airbnb Listings

Due to the different availability of data, we performed analysis of the distribution of Airbnb listings at two territorial levels: municipalities and tourist areas/sites. In the first approach, we used 8124 Spanish municipalities as units of analysis. They are varied in both area (between 1 km^2 and 1751 km^2) and population (between 5 persons and 3.2 million inhabitants). We counted Airbnb listings in each municipality using base map of administrative division [79]. At the municipal level, we used TripAdvisor data about the number of hotels as an indicator of tourism accommodation supply.

The second spatial unit of analysis are the tourist areas and sites defined by the Spanish Statistical Office (INE). They are areas with high concentration of tourist activity. Tourist sites are single municipalities, whereas tourist areas consist of multiple municipalities [80]. They do not cover the entire territory of Spain (see Figure A1 in Appendix C). We considered all 37 tourist areas defined by INE. Out of 106 tourist sites covered by INE statistics, we included 42 in our sample. We excluded those which are located within tourist areas, as well as those with small numbers of hotels for which data was protected by INE because of statistic secrecy. In the end, we took into account 79 tourism areas/sites in total.

2.3. Measuring Concentration and Spatial Autocorrelation of Airbnb Listings, Population and Hotel Supply

In order to numerically describe the level of spatial concentration of the supply of housing, hotel and peer-to-peer accommodation in Spanish municipalities, we employed the Hoover index. It is a widely used metric of spatial concentration, popular in population studies [81,82]. It is calculated as half of the sum of differences between shares of accommodation of each territorial unit (p_i, where i is the index of territorial unit) in total supply of accommodation in the country (P), and shares of area of each territorial unit in total area of the country (a_i and A respectively):

$$H = \frac{1}{2}\sum_i \mid p_i P^{-1} - a_i A^{-1} \mid \tag{1}$$

The value of the index equals 0 if the distribution of tourist accommodation is even across the country, and approaches 1 when it is concentrated in one small area. The value of the index can be interpreted as the share of the tourist accommodation that needs to be relocated to other units in order to obtain full uniformity of its distribution.

In an attempt to find out if municipalities with high concentrations of population, hotel and Airbnb offer cluster in specific areas, we used Moran I statistics of global univariate (formula (2)) and local univariate (formula (3)) spatial autocorrelation:

$$I = NS_0^{-1}(\Sigma_i \Sigma_j w_{ij} z_i z_j)(\Sigma_i z_i^2)^{-1} \tag{2}$$

$$I_i = z_i \Sigma_j w_{ij} z_j \tag{3}$$

where N represents the number of spatial units, i and j are their indexes, z is the deviation from mean ($z_i = x_i - \overline{x}$), and w_{ij} are spatial weights which sum up to S_0 ($S_0 = \Sigma_i \Sigma_j w_{ij}$) [83,84]. The calculation of Moran I depends of the way the spatial weights matrix is defined. In our study, we used the row-standardised queen-style contiguity weights matrix. Seven municipalities were excluded from the spatial autocorrelation analysis, as they do not have any neighbours.

For large samples, univariate global Moran I values higher than 0 indicate positive spatial autocorrelation, i.e., a tendency to cluster together high values in certain areas, and low values in other areas. Calculating univariate local Moran I for each territorial unit enables to produce maps of clusters based on the deviations of the variable values in given territorial unit and neighbouring units from the mean. High-high clusters are those where values for both given unit and neighbouring units are significantly higher than the mean, low-low clusters are the opposite. High-low outliers are areas with relatively high values surrounded by areas with low values, and low-high are the opposite.

Bivariate global and local Moran I enable to find out if the values of one variable in given spatial unit are correlated to the values of the second variable (lagged variable) in neighbouring spatial units. The general formula for global multivariate spatial correlation enables one to compute a variable by variable correlation coefficient matrix M based on data matrix Z including standardised values for n locations by m variables, its transpose Z^T, and spatial weights matrix W [85]:

$$M = Z^T W Z \tag{4}$$

Bivariate local Moran I is calculated similarly to univariate local Moran I, but instead of the values z_i and z_j of the same variable for different locations, $z_{k,i}$ is calculated based on the value of one variable (x_k) in location i, while $z_{l,j}$ is based on the value of the second, lagged, variable (x_l) in neighbouring location j [86]:

$$I_{kl,i} = z_{k,i} \Sigma_j w_{ij} z_{l,j} \tag{5}$$

To calculate spatial autocorrelation measures, we used densities of population, hotels and Airbnb listings per km^2. We performed this part of the analysis using GeoDa software [83].

2.4. Finding Factors That Explain the Distribution of Airbnb Listings

In order to identify the factors affecting the distribution of Airbnb listings in Spain, we developed a series of regression models. We built eight models: for each territorial unit of analysis (municipality and tourist areas/sites) and for each type of Airbnb listings (total listings, entire homes/apartments, private rooms, and shared rooms). In municipality models, we used densities of Airbnb listings of given type per square kilometre as explained variables, which helped to deal with data on municipalities of very diverse sizes. In the models for tourist areas/sites absolute numbers of Airbnb listings of given type served as explained variables. To each of the five hypotheses listed in Section 1, we assigned one or more explaining variables in regression models (Table 1). The descriptive statistics for all explained and explaining variables used in the models are presented in Appendix B.

Table 1. Explaining variables used in regression models.

Hypothesis	**Variables Used in Models for Municipalities (Explained Variables: Numbers of Listings per km^2)**	**Variables Used in Models for Tourist Areas/Sites (Explained Variables: Numbers of Listings)**
1. Supply of homes and flats	Number of primary dwellings per km^2 (Census, 2011)	Number of primary dwellings (Census, 2011)
	Number of nonprimary dwellings per km^2 (Census, 2011)	Number of nonprimary dwellings (Census, 2011)
2. Coastal location	Coastal location (1 for municipality which borders sea coast, 0 for other municipalities)	Coastal location (1 for tourist area/site which borders sea coast, 0 for other tourist areas/sites)
3. Supply of hotel accommodation	Number of hotels in TripAdvisor search engine per km^2 (2018)	Number of hotel rooms (Hotel occupancy survey, 2018)
4. Shortage of hotel capacity		Occupancy of hotel rooms (percent, average monthly value between XI 2017 and X 2018; Hotel occupancy survey)
		Seasonality ratio (ratio between the highest and the lowest monthly number of hotel guests between X 2017 and IX 2018; Hotel occupancy survey)
5. Access and presence of international tourists	Distance to the nearest airport (straight line in 100 km between airports with at least 50,000 passengers (2017) [87] and municipality border)	Distance to the nearest airport (for areas: average distance for all municipalities acknowledging the role of the extent of area; for sites: as for municipalities)
		Share of international tourists (percent among hotel guests; Hotel occupancy survey)

Because of the strongly asymmetric distribution of all explained variables, as well as some explaining variables, we used natural logarithms of their values in the models (Tables A2 and A3). In each model, we first introduced all explaining variables, and then performed their backward selection: we excluded insignificant factors until obtaining the best quality model measured by the maximum value of adjusted R^2 or minimum value of the Akaike Information Criterion (AIC). As several explaining variables in our model tend to be correlated, we also checked for multicollinearity by calculating variance inflation factors (VIF).

The values of Airbnb supply in municipalities are spatially autocorrelated (see Section 3.2). To remove the effect of spatial autocorrelation from model results, we included spatially lagged values of dependent variable as an explaining variable, thus creating spatial lag models [88,89] (also termed spatial autoregressive models [90]):

$$y = \rho Wy + X\beta + \varepsilon \tag{6}$$

Apart from simple linear model elements: dependent variable y, matrix of independent variables X, parameters vector β, and error term ε, the formula includes spatial weights matrix W (from row-standardised queen-style contiguity weights matrix), and spatial autoregressive parameter ρ (positive values denote a positive autocorrelation independent of explaining variables). In spatial lag models, we also excluded 7 municipalities which do not have any neighbours. We developed the models using R software with spdep [91] and regclass [92] packages.

For tourist areas/sites, we developed simple linear models not including the spatial effects. We did so because it was impossible to create a meaningful spatial weights matrix both based on neighbourhood (40 out of 79 units have no neighbours) and distance (sizes of units are very diverse, and geodesic distance may differ considerably from actual accessibility, e.g., in the case of islands).

3. Results

3.1. Distribution of Airbnb Listings

Out of 8124 Spanish municipalities, 4882 (60.1%) have at least one Airbnb listing, but most of municipalities have only a few of them. Airbnb offers are most numerous in large cities, as well as in municipalities located on the Mediterranean coast and in the Canary and Balearic Islands. In raw numbers, there are 1500 municipalities with 10 listings or more, 178 municipalities with at least 250 listings, and 45 municipalities with 1000 listings or more (Table 2).

Table 2. Numbers of Airbnb listings in Spanish municipalities.

Number of Listings	Number of Municipalities
14,520–16,509	2
2000–6616	14
1000–1999	29
500–999	59
250–499	74
100–249	136
10–99	1186
1–9	3382
0	3242

Map of the distribution of Airbnb listings (Figure 1) shows their concentration in large cities and in the areas with high tourist activity. A strip of municipalities with high numbers of listings stretches along the entire Mediterranean coast of Spain, as well as the coast of Cádiz. Apart from the largest coastal cities (Barcelona and Valencia), the quantity of listings is particularly high in the regions of Costa Brava (Catalonia), Costa Blanca (Valencia) and Costa del Sol (Málaga), as well as in the archipelagos: Canary Islands and Balearic Islands. All of them are popular sun-and-beach tourism destinations. In the northern part of Spain, the concentration of Airbnb listings is remarkable in traditional tourist areas of Sansenxo (Galicia) and San Sebastián (Basque Country).

Beyond coastal areas, Airbnb listings concentrate in mountain tourist destinations: Pyrenees, Sierra de Guadarrama, Sierra Nevada and Picos de Europa. All these areas are protected as national parks. The total numbers of offers are not as big there as in the cities and coastal municipalities, but they sprawl over large areas. The common form of accommodation in these places are spatially dispersed rural houses. Besides coastal and mountain areas, Airbnb offers are located in cities, particularly the largest ones: Barcelona, Madrid, Valencia, Sevilla and Málaga (Appendix C). Significant numbers of listings are also located in interior cities with important administrative and economic functions (e.g., Zaragoza), and in smaller cities with high numbers of tourist visits (e.g., Salamanca, Toledo).

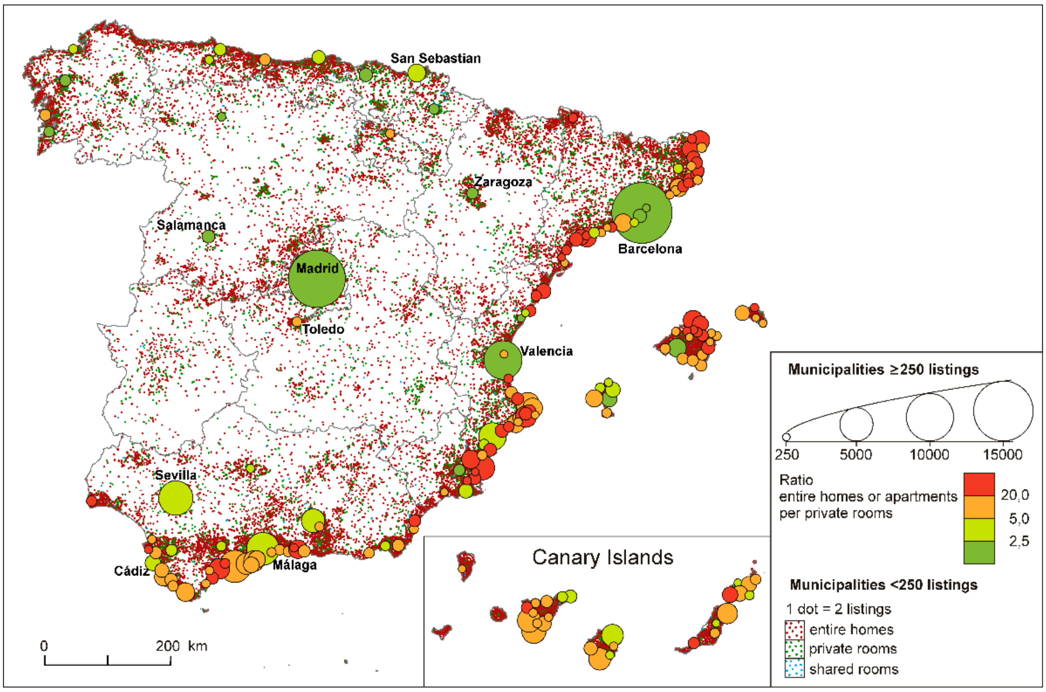

Figure 1. Distribution of Airbnb listings in Spanish municipalities.

There are some differences in the distribution of Airbnb listings of different types. Private rooms are particularly numerous in cities. In Barcelona, there is almost the same number of private rooms as entire properties. Traditional university cities, such as Salamanca or Santiago de Compostela, also have high proportion of private rooms. On the other hand, entire homes or apartments dominate in leisure tourist areas, especially in those areas where the tourist model has been historically oriented to second homes. In these cases, entire properties usually represent more than 90% of all listings (Appendix C). Similar structure characterises rural and mountain areas.

The distribution of absolute numbers of Airbnb listings may be misleading, since it is highly correlated with the distribution of population and housing. In Figure 2, we present the number of Airbnb listings per 1000 inhabitants in Spanish municipalities. These values are not the highest in the largest cities anymore. High numbers of listings per capita characterise coastal, mountain and rural leisure tourism areas. In Madrid and other major urban areas, the numbers of Airbnb listings per capita are similar or lower than the values for Pyrenees, Sierra Nevada, Sierra de Guadarrama mountains located north-west from Madrid metropolitan area, and eastern Asturias with popular tourist areas: Picos de Europa and Llanes. These regions, as well as many coastal areas, have low density of permanent population and their economies are highly reliant on tourism. High per capita numbers of Airbnb listings in such areas show that P2P rental accommodation is not only important for urban tourism.

The analysis of the distribution of Airbnb offers in tourist areas/sites shows the same distribution patterns as the municipal study (Figure 3, Table A4 in Appendix C). This territorial aggregation also allows us to compare the numbers of Airbnb listings with the capacity of hotel accommodation. In all tourist areas/sites combined, there are 218,222 Airbnb listings, which supplement the capacity of 765,532 hotel rooms. There are on average 285 listings per 1000 hotel rooms. In fact, the capacity of Airbnb properties is higher than this ratio suggests, as one listing can accommodate 4.83 persons on average (based on our web-scrapped database on listings), while hotel rooms house 2.09 persons on average (based on INE hotel occupancy survey). On the other hand, Airbnb places are probably less frequently occupied than hotel rooms.

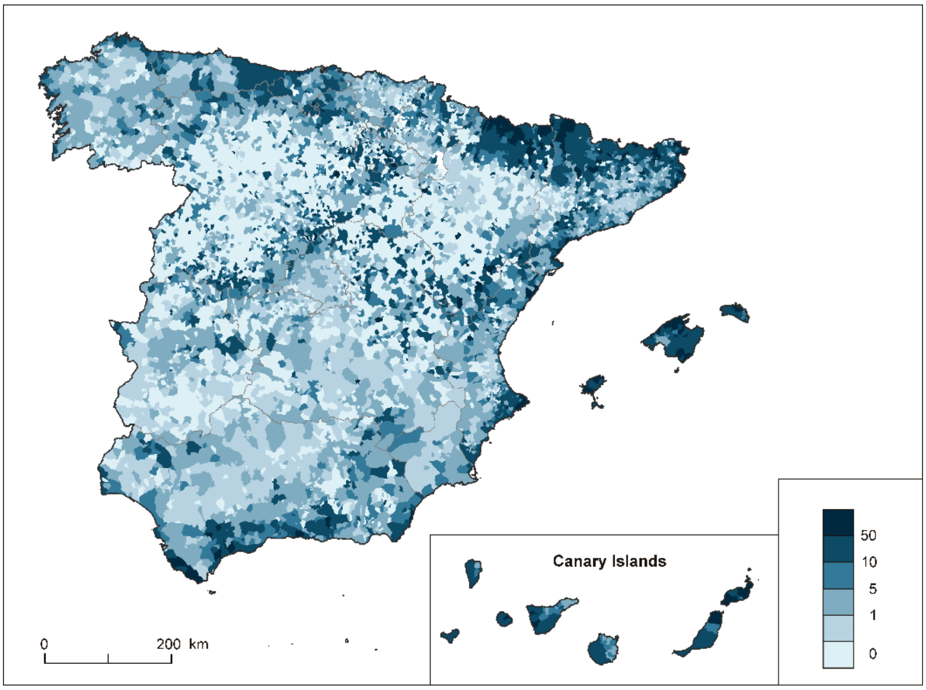

Figure 2. Number of Airbnb listings per 1000 inhabitants in Spanish municipalities.

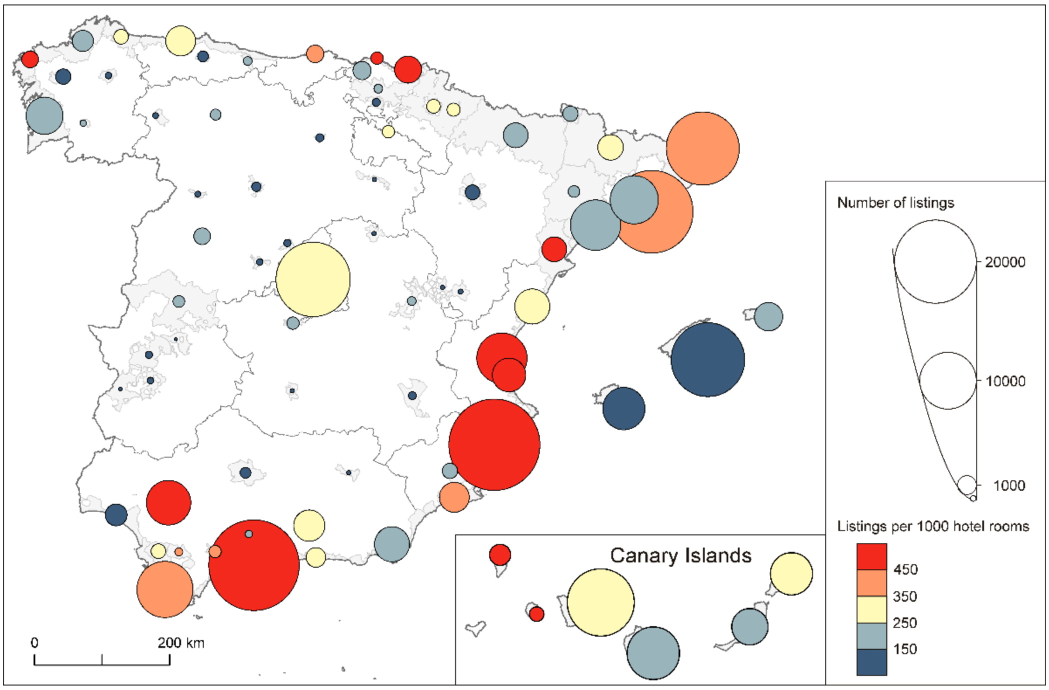

Figure 3. Number of Airbnb listings in Spanish tourist areas/sites.

The results show that the ratio of Airbnb listings per hotel rooms is high along the coasts, both in the Cantabrian and Mediterranean coasts. Costa del Sol (Málaga) and Costa Blanca (Comunitat Valenciana), both important residential tourism areas, are characterised by exceptionally high values of this proportion (over 500 Airbnb listings per 1000 hotel rooms). In the archipelagos, particularly in the Balearic Islands, Airbnb listings represent a lower share in the total accommodation capacity, due to very high numbers of hotels rooms. The exceptions are the islands of La Palma and La Gomera in Canary Islands, with high numbers of Airbnb listings compared to hotel rooms. In inland Spain, the proportion is usually lower than in coastal areas, even in the case of Madrid (323.6 Airbnb listings per 1000 hotel rooms).

3.2. Concentration and Spatial Autocorrelation of Airbnb Listings, Population and Hotel Supply

The Hoover index values prove the spatial concentration of population, hotel capacity and Airbnb listings in certain areas of the country (Table 3). The degree of concentration of traditional tourism accommodation is higher than of population. Nonprimary dwellings are more dispersed than primary dwellings across the country, because of a high number of nonpermanently inhabited rural houses, being a relic of historical, more dispersed distribution of population. Hotels and Airbnb listings have a similar degree of concentration. Nevertheless, there are some differences in the levels of concentration of different types of listings. Shared rooms are much more concentrated that entire homes/apartments, and private rooms are relatively dispersed.

Table 3. Level of spatial concentration of population, hotels, and Airbnb listings in Spanish municipalities.

Variable	Hoover Index
Population	0.688
Primary dwellings	0.682
Nonprimary dwellings	0.573
Hotels (from TripAdvisor)	0.815
Airbnb listings: total	0.802
Airbnb listings: entire homes/apartments	0.811
Airbnb listings: private rooms	0.801
Airbnb listings: shared rooms	0.920

Values of univariate global Moran I calculated for densities of population, two types of dwellings, hotels and Airbnb listings show that all of them have a significant tendency to cluster in certain areas (Table 4). Population and the distribution of primary dwellings are most strongly spatially autocorrelated. The lowest value of Moran I for the density of hotels is a result of a high number of municipalities with no hotels. The locations of clusters of high population, hotel and Airbnb listing density differ between each other (Figure 4). Population is clustered in major metropolitan areas, with low population clusters in large areas of inland Spain, including some mountainous areas like the Pyrenees. Hotel clusters are also located in major metropolitan areas as well as in important tourist coastal destinations, such as the Costa del Sol. Airbnb listings are clustered in the coastal strips of municipalities, and the archipelagos, i.e., the main sun and beach destinations of Spain. Nevertheless, important urban and metropolitan destinations, such as Madrid or Granada, are also marked as Airbnb listing clusters.

Table 4. Values of univariate global Moran I.

Variable	Moran I	Z-Value
Population	0.429	69.011 ***
Primary dwellings	0.419	68.017 ***
Nonprimary dwellings	0.355	54.481 ***
Hotels (from TripAdvisor)	0.088	15.929 ***
Airbnb listings: total	0.314	49.352 ***
Airbnb listings: entire homes/apartments	0.327	49.631 ***
Airbnb listings: private rooms	0.276	60.996 ***
Airbnb listings: shared rooms	0.107	19.769 ***

*** Significant at $p = 0.001$. Randomisation with 999 permutations.

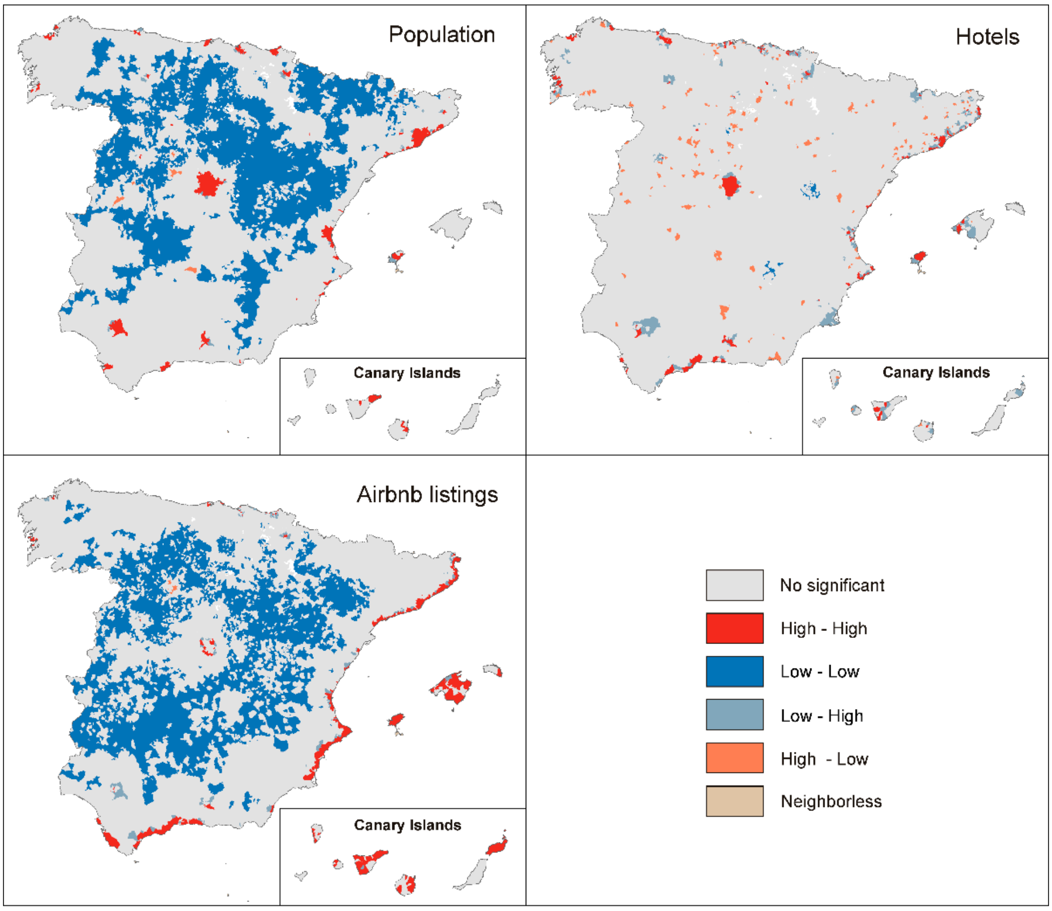

Figure 4. Cluster maps of univariate local Moran I.

The values of bivariate Moran I inform if the values of one variable are correlated with spatially lagged values of another variable. Table 5 shows that the distribution of hotels is spatially correlated with the distribution of population, and the distribution of Airbnb listings is spatially correlated with the distribution of both population and hotels. Cluster maps based on bivariate local Moran I make it possible to find out clusters of co-occurrence and outliers of spatial disparity between the variables (Figure 5). They confirm our previous observations. Hotels tend to be located in the same metropolitan clusters as the population, but many positive outliers (high density of hotels surrounded by low population density) are located in middle-size cities. Clusters of co-occurrence of Airbnb listings with population are present in metropolitan areas and some coastal parts of the country. Positive outliers (high density of Airbnb listings surrounded by low population density) are located in the Pyrenees, and negative outliers (low density of Airbnb listings surrounded by high population density) are present in suburban municipalities near big cities. Comparison between Airbnb listing density and spatially lagged hotel density shows that these two variables form common clusters. Still, there are many municipalities in the coastal regions, which have relatively high density of Airbnb listings, and are surrounded by areas with low density of hotels.

Table 5. Values of bivariate global Moran I.

Variable	Lagged Variable	Moran I	Z-Value
Hotels (from TripAdvisor)	Population	0.143	26.954 ***
Airbnb listings: total	Population	0.199	38.228 ***
Airbnb listings: total	Hotels (from TripAdvisor)	0.142	27.841 ***

*** Significant at $p = 0.001$. Randomisation with 999 permutations.

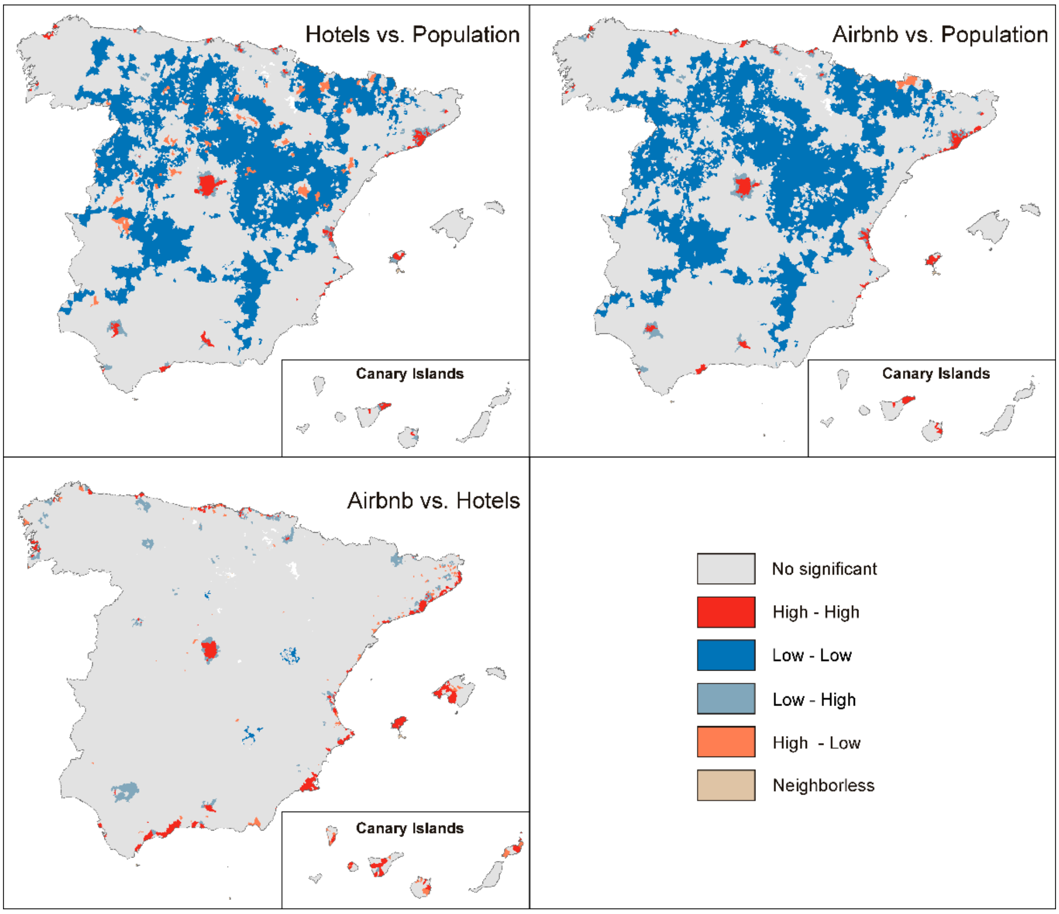

Figure 5. Cluster maps of bivariate local Moran I.

3.3. Factors Affecting the Distribution of Airbnb Listings

After developing four simple regression models at the municipal level, the majority of the explaining variables proved to significantly affect the dependent variables (Table A5 in Appendix D). This is partially a result of a large sample size. Despite correlation between various explaining variables, VIF values below 5 (Table A6 in Appendix D) show that multicollinearity does not bias our models [93]. Spatial lag models reveal the high impact of spatial autocorrelation (positive and statistically significant ρ values). Initial spatial lag models are presented in Table A7, and final models in Table 6.

Table 6. Final spatial lag models for municipalities (N = 8117).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
(Intercept)	−0.144 ***	−0.117 ***	−0.054 ***	−0.001
Primary dwellings (per km^2, ln)	−0.042 ***	−0.055 ***	0.004 *	-
Nonprimary dwellings (per km^2, ln)	0.133 ***	0.129 ***	0.023 ***	0.001 *
Coastal location	0.515 ***	0.530 ***	0.075 ***	0.008 ***
Number of hotels (per km^2, ln)	1.965 ***	1.802 ***	1.391 ***	0.159 ***
Distance to nearest airport (100 km)	-	-	0.007 *	-
ρ	0.553 ***	0.555 ***	0.506 ***	0.150 ***
AIC	−1080	−1518.5	−11497	−35,598
AIC for linear model	2413.9	1793.5	−9033.5	−35,491

Dependent variables: ln(listings/km^2). Significance scores: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p < 0.1$.

The results confirm the hypotheses of the impact of supply of apartments not used as primary dwellings, proximity to the principal tourism amenity of the sea coast, and presence of traditional tourism accommodation (hotels). Positive impact of the accessibility for international tourists measured by proximity to airports, which is visible in simple linear models (negative coefficient means that the further from the airport, the lower the number of Airbnb listings), was hidden under the autocorrelation effect in spatial lag models. An unexpected outcome is the negative and significant independent impact of the number of primary dwellings (though weaker than the positive impact of the number of nonprimary dwellings). This can be attributed to the influence of urban and suburban municipalities with high population, prevalence of primary dwellings and low tourism interest.

The municipal model for entire properties reflects the results of the one for total number of listings. In the model for private rooms, the number of primary dwellings becomes an independent factor positively affecting the results, which corroborates the hypothesis about the influence of supply of permanent residences on the number of rooms rented on Airbnb. According to the third model, numbers of hotels and nonprimary dwellings significantly positively affect the density of shared rooms.

Models for tourist areas/sites allow taking into account several new variables based on the data extracted from the hotel occupancy survey made by INE: number and occupancy of hotel rooms, seasonality of tourism and share of international tourists. Initial models with all variables included proved the need for limiting their sets in order to rid explaining variables with no significant effects (Table A8 in Appendix D). We should note, however, that besides low effect sizes, the much smaller sample in this set of models increased the significance thresholds for variables. Log-transformed numbers of primary and nonprimary dwellings are highly correlated (r = 0.911) causing VIF values reach 11.6. To avoid the problem of multicollinearity, we chose only one of these two variables (the one with higher absolute t value) for each model. After that, VIF analysis shows that coefficient estimates should not be biased by multicollinearity (Table A9 in Appendix D).

Final models for tourist areas/sites confirm the results obtained using data for municipalities (Table 7). The total number of listings is significantly positively affected by the amount of available nonprimary houses, coastal location, number of hotel rooms and the proximity to airports. Out of two variables added to the models to verify the hypothesis about the shortage of hotel capacity as a driver of Airbnb presence, neither tourism seasonality, nor occupancy ratio have an independent significant effect. New models confirmed that the number of Airbnb listings is positively affected not only by the accessibility for international tourist measured as negative distance to the nearest airport, but also by the actual share of international tourists in overall number of tourists.

Table 7. Final linear models for tourist areas/sites (N = 79).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
(Intercept)	−2.549 ***	−2.888 ***	−3.640 ***	−3.264 ***
Primary dwellings (ln)	-	-	0.257 **	-
Nonprimary dwellings (ln)	0.213 **	0.171 ˙	-	-
Coastal location	0.558 ***	0.781 ***	-	0.366
Number of hotel rooms (ln)	0.737 ***	0.788 ***	0.715 ***	0.671 ***
Occupancy of hotel rooms	-	-	−0.019 *	-
Seasonality ratio (ln)	-	-	−0.231 ˙	−0.316 *
Distance to nearest airport (100 km)	−0.340 *	−0.251	−0.421 **	−0.538 *
Share of international tourists (ln)	0.278 ˙	0.254	0.394 *	-
Residual standard error	0.496	0.580	0.549	0.816
Adjusted R^2	0.920	0.900	0.877	0.675
F-statistic	179.0 ***	141.0 ***	93.2 ***	41.5 ***

Significance scores: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ˙ $p < 0.1$.

There are differences in the sets of factors affecting the distribution of each of the three kinds of Airbnb accommodation in tourist areas/sites. As we expected, private rooms are more numerous in the areas of high supply of permanent dwellings. Unlike in the municipalities model, the effect of the number of primary dwellings is stronger than the effect of the number of nonprimary dwellings. Coastal location strongly affects the distribution of entire properties, but not private rooms. The model for private rooms includes occupancy of hotel rooms and seasonality (the latter variable is also present in the model for shared rooms), but the effect is the opposite of what we assumed: low occupancy and seasonality lead to the increase in private room supply. Proximity to airport significantly affects the distribution of private rooms, while its impact on the number of entire homes/apartments does not reach the statistical significance threshold. A similar pattern can be observed in case of the share of international tourists. These differences stem from the fact that entire properties are more concentrated in vacation coastal locations, while rooms tend to be more often located in cities.

4. Discussion and Conclusions

The research shows that the distribution of about 250,000 properties offered for rent through the Airbnb platform in Spain follows the general patterns of the distribution of population and hotel accommodation. Airbnb listings are mostly concentrated in major cities, coastal areas and in the Balearic and Canary Islands. Therefore, tourist accommodation offered through P2P platforms does not contribute to the territorial deglomeration of tourist activity at the country scale, as it does not contribute to the territorial deglomeration of tourist activity at the local scale in urban areas and nature-based tourism areas [32,33,66]. On the contrary, the possible revenue from Airbnb rental encourages the growth of the tourist accommodation offer in places of high demand, which contributes to the concentration of tourism activity in already existing hotspots.

Airbnb listings, mostly entire homes and apartments, concentrate in tourism areas which follow the model of sun-and-beach residential tourism development [94,95]. This is supported by the results of the regression analysis: the number of Airbnb rentals is positively affected by coastal location, high number of nonprimary dwellings and hotel accommodation supply. In these areas, P2P accommodation platforms provide a new way of commercializing tourist accommodation in homes or apartments already used for touristic purposes either privately (second homes) or commercially. In coastal tourist areas, numbers of Airbnb listings are much higher than the numbers of legally registered holiday dwellings, according to the Holiday Dwellings Occupancy Survey [78]. It is difficult to say to what degree Airbnb is used to commercialise the already existing, either registered or not, stock of holiday dwellings. The lack of such data hampers the full understanding of the impact of P2P platforms on the development of tourism destinations. In any case, this new way of commercialisation of vacation dwellings can increase the intensity of use of the accommodation stock and open new business opportunities for the tourism sector [68,96].

The above conclusions apply to the entire homes/apartments rented trough Airbnb platform, which are the majority (81.7%) of listings. The supply of private and shared rooms has different characteristics. It does not concentrate in residential tourism areas, but mainly in big and medium-sized cities. Therefore, it is more related to the housing market dynamics of these cities and to urban and cultural tourism models. The two types of Airbnb offer (entire homes/apartments and private rooms) should be treated separately, as they have different distribution and exert different impacts on the territory and the society. Whereas P2P platforms are mainly a way to commercialise vacation rentals and second homes in residential tourism areas, in cities, the use of these platforms appears to be slightly closer to the original "sharing economy" model, where owners rent out a room in their houses, obtaining an extra income in exchange for the service provided. However, we do not know if all private and shared rooms offered on Airbnb are parts of houses inhabited by their owners, or they are rather parts of houses or apartments in which all rooms are rented out. Further research should explore these issues in detail. Also, urban Airbnb rentals can not only serve tourist demand (short rentals), but may be also used to supply housing for permanent or temporal residents.

Although Airbnb listings mostly concentrate around tourist hotspots, our research has shown that Airbnb supply is spread over the entire Spanish territory, including mountain and rural areas. Airbnb is far from being only an urban phenomenon, despite the urban focus of most studies on the topic to date [32–38]. More studies assessing the impact of P2P accommodation platforms on nonurban areas are needed. The distinction of different kinds of location of Airbnb rental activity (big cities, coastal tourist areas, rural areas) is useful in designing policy response to this phenomenon. Significant differences in the size, structure, and role of peer-to-peer rental supply in various types of settlements and tourist destinations must lead to different impacts on the housing and tourism markets. These impacts should be addressed by policies adjusted to the regional and local conditions. Such policies need to be informed by studies focused on specific local environments and should address multiple issues, such as the competition of P2P rentals with other tourism accommodation providers, the effects on housing supply and demand or the effects on employment and entrepreneurship.

Our study does not provide an unambiguous answer to the question whether P2P accommodation competes with or complements the tourism accommodation offered by hotels and other traditional establishments. As stated above, many Airbnb offers in residential tourism destinations might be homes and apartments that have already been used privately for tourism purposes, or offered for rent to tourists using other distribution channels. This applies particularly to the coast of Andalucía and Comunitat Valenciana, with the highest stocks of vacation rentals [97], and not so much to the archipelagos, where the numbers of hotel beds are much higher than those located in holiday apartments. Second homes also form a significant part of tourism accommodation in rural tourism areas [98], and our results suggest that such homes are also being commercialised through P2P platforms. Still, the numbers of Airbnb listings in these areas are low compared to the numbers of hotel rooms. Accordingly, no serious competition can be seen yet between P2P platforms and traditional commercial tourist accommodation offer in this kind of areas.

We have not proven positive correlation between the number of Airbnb listings and the shortage of hotel capacity, which would suggest that Airbnb capacity supplements the supply of tourism accommodation in places where it is most needed. The spatial correlation between the location of Airbnb listings and hotel accommodation is high, though not perfect. Their numbers differ in some residential tourism areas with low supply of hotel accommodation, and in some cities which are not important leisure tourism destinations, where the size of Airbnb offer is much smaller than hotel capacity. In such places, P2P platforms and the traditional hotel sector play a complementary role, which is consistent with the conclusions of previous studies in the field [7,9]. Previous studies at the local scale conclude that even if P2P accommodation locates in the same areas as hotels [33,60,99], their offer may be targeted to different customers. In fact, Airbnb seems to compete mostly against hotels and other accommodation services of lower categories, but not against high-end hotels [10,13,58].

The interpretation of the study results has several limitations. First, we used data on Airbnb, which is the largest, but only one of several platforms that enable peer-to-peer rental of flats for tourist purposes. Comparative data show high correlation in territorial distribution of offers on various platforms [100], yet some differences may exist. Airbnb is a platform used often by international and urban tourists [52,101,102], while domestic tourists may use other platforms as well. Rural tourism establishments traditionally use other web portals [103,104], which may also be used to commercialise rental houses in these areas. Second, we measured only the supply of Airbnb accommodation, which reflects the homeowners' decisions to rent out a property, but not their actual use. We do not use the numbers of reviews obtained by individual listings, but other authors have tested using this data as a proxy for the intensity of the use of P2P accommodation establishments [57,58]. Finally, the web scrapping technique that we have employed omitted some of the Airbnb listings, which could lead to the underrating of the absolute numbers of listings (see Appendix A). However, it is unlikely that it has distorted the proportions of listings across types and locations.

Future directions of spatial studies on peer-to-peer accommodation should include other platforms and look for spatial regularities in other characteristics than the size of supply, like occupancy, ratings and prices. Such studies are already performed on lower, particularly urban spatial scales, but large-scale analysis on country or international levels will be more fruitful in finding determinants of spatial variability, including type of environment and cultural and political factors. Advanced techniques of spatial analysis, and the use of geometric spatial units of analysis, should also be moved from urban and regional scale to larger areas of interest.

Our research is an example of a study based on nonconventional sources of spatial statistical data. Such approaches are increasingly popular in studies on population and tourism. Data obtained from online sources, such as online travel agencies [72], social media [105] or search engines [106], are used to describe and predict tourist activity with higher spatial and temporal precision than it is possible based on conventional statistical data provided by public statistical institutions. Keeping in mind that Airbnb data does not reflect the entire tourism mobility (as shown in the paper, it exaggerates the role of international tourism), it can also be used as a tool enabling comparative studies on spatial patterns of tourism activity on the international scale. Thanks to the data on the numbers of reviews, it can also serve to investigate the temporal variability of tourism activity with a high level of geographic detail.

Finally, the analysis contributes to wider debates on the nature of tourist accommodation and tourism itself from a geographical perspective. Together with second homes, VFR (visiting friends and relatives) tourism, cruise tourism or recreational vehicles, peer-to-peer accommodation is located at the peripheries of the notion of tourist accommodation, the centre of which is occupied by hotels. Hotels are fixed in space, (relatively) constant in time, often located based on the negotiations between public and private institutions realised through the planning process, and designed following globalised trends and the pursuit of comfort and organisational efficiency. Peer-to-peer accommodation platforms oppose this model in many ways: such tourism accommodation establishments are "invisible", volatile in time and space and flexibly adjust to market situations, offering variety and uniqueness, which are primary qualities sought after by customers. Dealing with dispersed, volatile, or mobile, forms of accommodation is challenging for spatial studies, but necessary to understand the complex nature of tourism mobility.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A Web Scrapping Procedure

We collected data on Airbnb listings using a Python script published by Tom Slee [77]. The script accesses the Airbnb website, searching for the listings located within a given set of coordinates and saves the following information about the resulting offers in a database: listing type, approximate address, number of reviews and average review score, capacity, numbers of bedrooms and bathrooms, price, and coordinates.

Some of the listings have wrong coordinates in the platform and appear to be located offshore or outside of Spain, despite having a Spanish address. We have cleaned the database of such falsely located listings, ruling out those listings which were not located in the Spanish territory. After this step, we gathered 247,456 records.

We evaluated the completeness of our data collection by comparing it with the information from three other services gathering data on Airbnb offer: Inside Airbnb, DataHippo and AirDNA (Table A1). Inside Airbnb is a nonprofit website that publishes datasets with information on Airbnb listings for various cities of the world, including the Barcelona, Madrid, Málaga and Sevilla in Spain [107]. DataHippo is another nonprofit project that gathers data on offers of Airbnb and three other P2P rental platforms for Spain, Portugal and Andorra [100]. It has been collecting data continuously for a year, which results in a large list of offers, including listings that are not available for rent anymore. Finally, AirDNA is a commercial service offering information on Airbnb market that uses advanced technology for web monitoring, which enables one to filter out inactive Airbnb offers [108].

The author of the script states that the data collection method may underrate the number of listings by up to 20% [77]. Indeed, the number of Airbnb records we have gathered is on average 7% lower than the most recent data of Inside Airbnb and a 29% lower than the one scrapped by DataHippo. The difference between our data and data of AirDNA is very low on average, although the numbers for individual cities differ by up to 9%.

Table A1. Comparison of numbers of Airbnb listings in Spanish cities according to various sources.

City	Authors (October 2018)	Inside Airbnb	DataHippo (September 2017–September 2018)	AirDNA (November 2018)
Barcelona	16,509	18473 (10 October 2018)	27,503	18,093
Madrid	14,520	17303 (10 October 2018)	24,976	15,229
Valencia	6616	-	9394	6420
Sevilla	5252	4746 (18 October 2018)	7423	5583
Málaga	4927	5549 (29 September 2018)	6419	5002
Marbella	4677	-	6234	3945
Alacant	3561	-	4522	3444
Arona	2607	-	3457	2693
Granada	2559	-	3748	2742
Torrevieja	2531	-	3335	2397

Appendix B Descriptive Statistics of the Variables Used in Regression Models

Table A2. Descriptive statistics of the variables used in models for municipalities (N = 8124).

Variable	Min	Median	Mean	Max	SD	Transformation
Total listings per km^2	0	0.025	0.665	163.57	4.352	ln(x + 1)
Entire homes/apartments per km^2	0	0.017	0.548	101.56	3.581	ln(x + 1)
Private rooms per km^2	0	0	0.113	79.768	1.147	ln(x + 1)
Shared rooms per km^2	0	0	0.003	2.372	0.044	ln(x + 1)
Primary dwellings per km^2	0.102	6.022	66.704	10189.7	348.95	ln(x + 1)
Nonprimary dwellings per km^2	0	5.272	23.821	1840.1	88.664	ln(x + 1)
Coastal location	0	0	0.058	1	0.233	x
Number of hotels per km^2	0	0	0.015	6.350	0.133	ln(x + 1)
Distance to nearest airport (100 km)	0	0.653	0.728	2.757	0.468	x

Table A3. Descriptive statistics of the variables used in models for tourist areas/sites (N = 79).

Variable	Min	Median	Mean	Max	Sum	SD	Transformation
Total listings	25	582	2762	21,921	218,222	4858	ln(x)
Entire homes/apartments	18	422	2275	20,130	179,757	4108	ln(x)
Private rooms	6	105	472	8674	37,292	1148	ln(x)
Shared rooms	0	4	15	184	1173	31	ln(x + 1)
Primary dwellings (thous.)	0.4	64.6	143	1321	11280	223	ln(x)
Nonprimary dwellings (thous.)	0.4	21.2	52.1	404	4115	69.2	ln(x)
Coastal location	0	0	0.42	1	33	0.50	x
Number of hotel rooms (thus.)	0.31	2.28	9.69	125	766	17.7	ln(x)
Occupancy of hotel rooms	26.9	50.9	50.2	77.9		11.9	x
Seasonality ratio	1.27	2.60	4.51	43.8		5.9	ln(x)
Distance to nearest airport (100 km)	0	0.41	0.55	2.12		0.52	x
Share of international tourists	8.7	26.5	34.4	89.6		22.2	ln(x)

Appendix C Airbnb Accommodation Supply in Tourist Areas/Sites

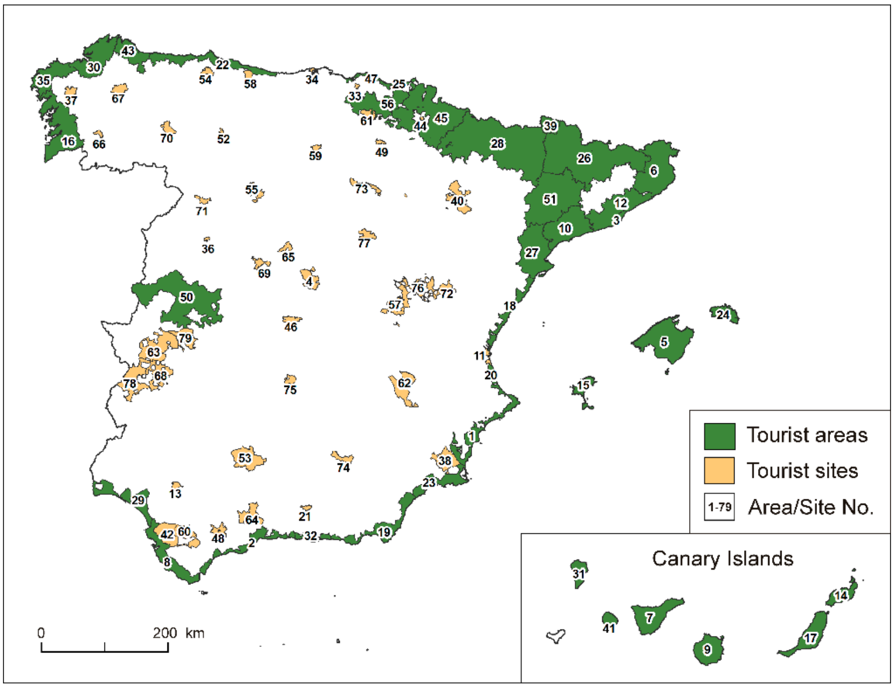

Figure A1. Location of tourist areas/sites described in Table A4.

Table A4. Airbnb accommodation supply in tourist areas/sites.

Area/Site No.	Type	Name	Area (km^2)	Population (2017)	Hotel Rooms (2018)	Airbnb Listings:				Ratio Entire Homes or Apartments per Private Rooms	Airbnb Listings per:		
						Total	Entire Homes/ Apartments	Private Rooms	Shared Rooms		km^2	1000 Inhabitants	1000 Hotel Rooms
1	Area	Comunitat Valenciana: Costa Blanca	1680	1,076,962	35,867	21,921	20,130	1758	33	11.5	13.0	20.4	611.2
2	Area	Andalucía: Costa Del Sol (Málaga)	1226	1,247,984	40,969	21,476	19,680	1758	38	11.2	17.5	17.2	524.2
3	Area	Cataluña: Barcelona	147	2,248,227	43,061	17,871	9048	8674	149	1.0	121.4	7.9	415.0
4	Site	Madrid	607	3,182,981	44,874	14,520	9671	4665	184	2.1	23.9	4.6	323.6
5	Area	Baleares (Illes): Isla De Mallorca	3723	868,693	125,221	14,417	13,135	1270	12	10.3	3.9	16.6	115.1
6	Area	Cataluña: Costa Brava	3945	658,821	37,768	14,035	13,129	888	18	14.8	3.6	21.3	371.6
7	Area	Canarias: Isla De Tenerife	2068	894,636	39,872	11,935	10,714	1127	94	9.5	5.8	13.3	299.3
8	Area	Andalucía: Costa De La Luz De Cádiz	2059	832,516	19,344	8389	7354	989	46	7.4	4.1	10.1	433.7
9	Area	Canarias: Isla De Gran Canaria	1583	843,158	29,591	7223	6167	978	78	6.3	4.6	8.6	244.1
10	Area	Cataluña: Costa Daurada	3046	612,185	28,004	6674	6150	506	18	12.2	2.2	10.9	238.3
11	Site	Valencia	141	787,808	9061	6616	4566	2027	23	2.3	47.0	8.4	730.2
12	Area	Cataluña: Costa Barcelona 2016	3036	2,825,766	30,334	6172	4582	1558	32	2.9	2.0	2.2	203.5
13	Site	Sevilla	141	689,434	11,284	5252	4031	1204	17	3.3	37.1	7.6	465.4
14	Area	Canarias: Isla De Lanzarote	853	147,023	15,989	4740	4308	403	29	10.7	5.6	32.2	296.5
15	Area	Baleares (Illes): Islas De Ibiza-Formentera	666	156,136	31,404	4677	3716	934	27	4.0	7.0	30.0	148.9
16	Area	Galicia: Rías Baixas (Pontevedra y A Coruña)	3700	990,021	16,195	3624	2993	596	35	5.0	1.0	3.7	223.8
17	Area	Canarias: Isla De Fuerteventura	1675	110,299	21,739	3486	3136	275	75	11.4	2.1	31.6	160.4
18	Area	Comunitat Valenciana: Costa de Castellón	931	362,728	9798	3303	3005	292	6	10.3	3.5	9.1	337.1
19	Area	Andalucía: Costa De Almería	1875	491,612	15,045	3242	2977	261	4	11.4	1.7	6.6	215.5
20	Area	Comunitat Valenciana: Costa Valencia	573	353,799	5350	2946	2710	232	4	11.7	5.1	8.3	550.7
21	Site	Granada	88	232,770	7576	2559	1948	607	4	3.2	28.9	11.0	337.8
22	Area	Asturias (Principado De): Costa Verde	2080	480,971	7706	2412	2017	371	24	5.4	1.2	5.0	313.0
23	Area	Murcia (Región De): Costa Cálida	1286	371,642	5720	2395	2139	246	10	8.7	1.9	6.4	418.7
24	Area	Baleares (Illes): Isla De Menorca	714	91,170	13,699	2194	1997	182	15	11.0	3.1	24.1	160.2
25	Area	Pais Vasco: Costa Guipuzkoa	229	272,161	3717	1945	1478	458	9	3.2	8.5	7.1	523.3
26	Area	Pirineus	9164	195,529	6832	1762	1447	309	6	4.7	0.2	9.0	257.9
27	Area	Cataluña: Terres de l'Ebre	3350	179,508	2559	1659	1543	113	3	13.7	0.5	9.2	648.3
28	Area	Pirineo Aragonés	10,694	58,094	7237	1651	1419	223	9	6.4	0.2	28.4	228.1
29	Area	Andalucía: Costa De La Luz (Huelva)	1695	158,722	10,735	1290	1206	82	2	14.7	0.8	8.1	120.2
30	Area	Galicia: Rías Altas (A Coruña)	2531	623,663	6105	1185	938	241	6	3.9	0.5	1.9	194.1
31	Area	Canarias: Isla De La Palma	722	81,350	2057	1160	1058	91	11	11.6	1.6	14.3	563.9
32	Area	Andalucía: Costa Tropical (Granada)	441	115,669	3355	1025	958	66	1	14.5	2.3	8.9	305.5
33	Site	Bilbao	42	345,110	4147	847	438	399	10	1.1	20.4	2.5	204.2
34	Site	Santander	36	171,951	2282	814	605	207	2	2.9	22.5	4.7	356.7
35	Area	Galicia: Costa Da Morte (A Coruña)	1718	114,561	1423	739	678	52	9	13.0	0.4	6.5	519.3
36	Site	Salamanca	39	144,436	2964	712	427	277	8	1.5	18.1	4.9	240.2
37	Site	Santiago de Compostela	220	96,456	4218	615	422	188	5	2.2	2.8	6.4	145.8
38	Site	Murcia	894	443,243	2502	614	385	219	10	1.8	0.7	1.4	245.4
39	Area	Cataluña: Vall d'Aran	640	9985	3040	605	554	51	0	10.9	0.9	60.6	199.0
40	Site	Zaragoza	983	664,938	5571	582	379	198	5	1.9	0.6	0.9	104.5
41	Area	Canarias: Isla De La Gomera	375	20,976	903	581	536	45	0	11.9	1.5	27.7	643.4

Table A4. *Cont.*

42	Site	Jerez de la Frontera	1189	212,915	1839	574	415	157	2	2.6	0.5	2.7	312.1
43	Area	Galicia: Costa A Mariña Lucense (Lugo)	1396	71,471	1842	567	494	72	1	6.9	0.4	7.9	307.8
44	Site	Pamplona/Iruña	25	197,138	1823	534	256	243	35	1.1	21.1	2.7	292.9
45	Area	Pirineo Navarro	5950	92,054	1575	442	318	110	14	2.9	0.1	4.8	280.6
46	Site	Toledo	233	83,741	2240	429	365	63	1	5.8	1.8	5.1	191.5
47	Area	Pais Vasco: Costa Bizkaia	248	200,823	743	428	313	105	10	3.0	1.7	2.1	576.0
48	Site	Ronda	398	34,268	1171	421	343	76	2	4.5	1.1	12.3	359.5
49	Site	Logroño	79	150,979	1383	383	321	57	5	5.6	4.8	2.5	276.9
50	Area	Extremadura: Norte de Extremadura	6342	161,995	2284	352	274	78	0	3.5	0.1	2.2	154.1
51	Area	Cataluña: Terres de Lleida	5664	361,138	2032	343	238	102	3	2.3	0.1	0.9	168.8
52	Site	León	39	125,317	2089	333	221	103	9	2.1	8.5	2.7	159.4
53	Site	Córdoba	1258	325,916	3699	318	247	71	0	3.5	0.3	1.0	86.0
54	Site	Oviedo	187	220,301	2934	314	227	87	0	2.6	1.7	1.4	107.0
55	Site	Valladolid	198	299,715	2131	227	92	133	2	0.7	1.1	0.8	106.5
56	Area	Pirineo Vasco	2590	208,100	1215	203	120	80	3	1.5	0.1	1.0	167.1
57	Site	Cuenca	917	54,876	1092	201	166	34	1	4.9	0.2	3.7	184.1
58	Site	Cangas de Onís	214	6332	1258	190	164	22	4	7.5	0.9	30.0	151.0
59	Site	Burgos	107	175,623	2065	177	114	63	0	1.8	1.6	1.0	85.7
60	Site	Arcos de la Frontera	528	30,983	449	169	131	38	0	3.4	0.3	5.5	376.4
61	Site	Vitoria-Gasteiz	278	246,976	1563	159	63	96	0	0.7	0.6	0.6	101.7
62	Site	Albacete	1135	172,816	1237	156	51	104	1	0.5	0.1	0.9	126.1
63	Site	Cáceres	1751	95,917	1257	151	115	33	3	3.5	0.1	1.6	120.1
64	Site	Antequera	750	41,104	739	147	120	26	1	4.6	0.2	3.6	198.9
65	Site	Segovia	164	51,756	1273	128	97	31	0	3.1	0.8	2.5	100.5
66	Site	Ourense	85	105,636	728	114	79	31	4	2.5	1.3	1.1	156.6
67	Site	Lugo	330	97,995	962	110	64	46	0	1.4	0.3	1.1	114.3
68	Site	Mérida	866	59,187	995	110	71	39	0	1.8	0.1	1.9	110.6
69	Site	Ávila	231	58,149	1403	104	76	28	0	2.7	0.4	1.8	74.1
70	Site	Ponferrada	283	65,788	720	101	69	32	0	2.2	0.4	1.5	140.3
71	Site	Zamora	149	62,389	640	92	74	18	0	4.1	0.6	1.5	143.8
72	Site	Teruel	444	35,484	934	69	63	6	0	10.5	0.2	1.9	73.9
73	Site	Soria	273	38,881	657	55	44	11	0	4.0	0.2	1.4	83.7
74	Site	Cazorla	307	7613	421	53	45	8	0	5.6	0.2	7.0	125.9
75	Site	Ciudad Real	286	74,641	803	51	33	18	0	1.8	0.2	0.7	63.5
76	Site	Albarracín	456	1044	308	45	26	19	0	1.4	0.1	43.1	146.1
77	Site	Sigüenza	389	4496	308	45	35	9	1	3.9	0.1	10.0	146.1
78	Site	Badajoz	1441	150,543	1111	37	21	16	0	1.3	0.0	0.2	33.3
79	Site	Trujillo	650	9274	491	25	18	7	0	2.6	0.0	2.7	50.9

Appendix D Additional Tables for Regression Models

Table A5. Initial linear models for municipalities (N = 8124).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
(Intercept)	−0.169 ***	−0.140 ***	−0.077 ***	−0.001
Primary dwellings (per km^2, ln)	−0.004	−0.031 ***	0.028 ***	0.000
Nonprimary dwellings (per km^2, ln)	0.162 ***	0.162 ***	0.025 ***	0.001
Coastal location	0.851 ***	0.869 ***	0.117 ***	0.008 ***
Number of hotels (per km^2, ln)	2.090 ***	1.884 ***	1.515 ***	0.162 ***
Distance to nearest airport (100 km)	−0.051 ***	−0.041 ***	−0.009 *	−0.001
Adjusted R^2	0.678	0.653	0.566	0.172

Dependent variables: ln(listings/km^2). Significance scores: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ˙ $p < 0.1$.

Table A6. Variance inflation factors for linear models for municipalities (N = 8124).

	VIF
Primary dwellings (per km^2, ln)	4.833
Nonprimary dwellings (per km^2, ln)	4.655
Coastal location	1.277
Number of hotels (per km^2, ln)	1.205
Distance to nearest airport (100 km)	1.277

Table A7. Initial spatial lag models for municipalities (N = 8117).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
(Intercept)	−0.146 ***	−0.120 ***	−0.054 ***	–0.001
Primary dwellings (per km^2, ln)	−0.041 ***	−0.055 ***	0.004 *	−0.000
Nonprimary dwellings (per km^2, ln)	0.132 ***	0.129 ***	0.023 ***	0.001
Coastal location	0.516 ***	0.530 ***	0.075 ***	0.008 ***
Number of hotels (per km^2, ln)	1.965 ***	1.802 ***	1.391 ***	0.159 ***
Distance to nearest airport (100 km)	0.003	0.003	0.007 *	−0.000
ρ	0.553 ***	0.555 ***	0.506 ***	0.150 ***
AIC	−1078.2	−1516.7	−11497	−35594
AIC for linear model	2371.5	1763.6	−9033.5	−35490

Dependent variables: ln(listings/km^2). Significance scores: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ˙ $p < 0.1$.

Table A8. Initial linear models for tourist areas/sites (N = 79).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
(Intercept)	−2.088 **	−2.375 **	−3.773 ***	−2.793 *
Primary dwellings (ln)	−0.347 **	−0.537 ***	0.218	−0.082
Nonprimary dwellings (ln)	0.539 ***	0.708 ***	0.062	−0.195
Coastal location	0.462 **	0.589 **	0.062	0.450
Number of hotel rooms (ln)	0.753 ***	0.765 ***	0.696 ***	0.809 ***
Occupancy of hotel rooms	−0.004	−001	−0.018 ˙	−0.020
Seasonality ratio (ln)	−0.111	−0.093	−0.222 ˙	−0.424 *
Distance to nearest airport (100 km)	−0.483 ***	−0.484 **	−0.439 **	−0.492 *
Share of international tourists (ln)	0.393 *	0.414 *	0.417 *	0.164
Adjusted R^2	0.926	0.917	0.873	0.668

Dependent variables: ln(listings). Significance scores: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ˙ $p < 0.1$.

Table A9. Variance inflation factors for final models for tourist areas/sites (N = 79).

	Total Listings	Entire Homes/Apartments	Private Rooms	Shared Rooms
Primary dwellings (ln)	-		3.515	-
Nonprimary dwellings (ln)	3.633	3.633	-	-
Coastal location	1.667	1.667	-	1.815
Number of hotel rooms (ln)	5.348	5.348	5.546	1.742
Occupancy of hotel rooms	-	-	3.014	-
Seasonality ratio (ln)	-	-	1.867	1.261
Distance to nearest airport (100 km)	1.547	1.547	1.668	1.424
Share of international tourists (ln)	2.523	2.523	3.048	-

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